Journal of Applied Economic Sciences
Volume XX, Fall, Issue 3(89), 2025

State Beveridge Curve Shifts during the Great Recession

Aaron POPP
https://orcid.org/0000-0002-8318-9536
Department of Economics
California State University, Fullerton, California, United States of America
apopp@fullerton.edu

Article's history:

Received 23rd of June, 2025; *Revised* 29th of July, 2025; *Accepted* 12th of August, 2025; *Available online*: 30th of September, 2025. *Published* as article in the Volume XX, Fall, Issue 3(89), 2025.

Copyright© 2025 The Author(s). This article is distributed under the terms of the license CC-BY 4.0., which permits any further distribution in any medium, provided the original work is properly cited.

Suggested citation:

Popp, A. (2025). State Beveridge Curve Shifts during the Great Recession. *Journal of Applied Economic Sciences*, Volume XX, Fall, 3(89), 401 – 425. https://doi.org/10.57017/jaes.v20.3(89).04

Abstract:

This paper estimates the size and timing of state-level shifts of the Beveridge Curve to examine changes in US labour market conditions during the Great Recession. Compared to a benchmark based on each state's share of unemployed, states in the Southwest, Southeast, and Mid-Atlantic experienced excess shifts. The timing of the shifts is heterogeneous, with 35 states shifting between November, 2009 and March, 2010. Regression evidence shows that population growth, higher construction and natural resource employment, house price appreciation, and urbanization explain the size of the state shifts, which suggests that diverse factors contributed to the shifts in the Beveridge curve.

Keywords: Beveridge curve, Great Recession, decomposition, skills mismatch, geographic mismatch.

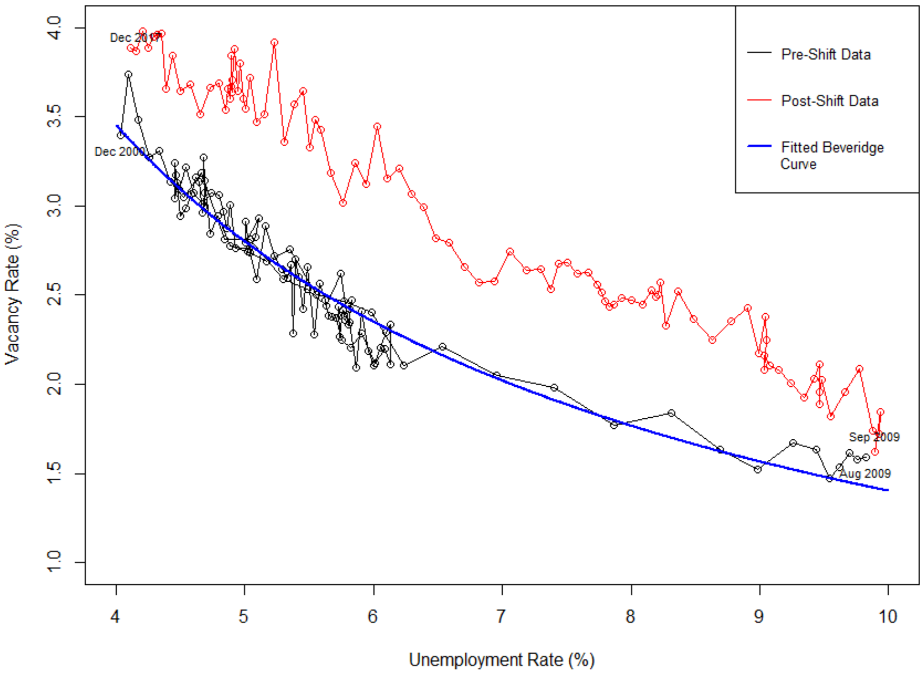
JEL Classification: E24; J63; J64; R12.

Introduction

The Beveridge curve is the inverse relationship between the unemployment rate and the vacancy rate in many developed countries' labour market data, including for the United States as shown in Figure 1.

Two of its features help macroeconomists organize their study of the labour market. First, a stable relationship can persist for years, such as for the December, 2000 to August, 2009 data in Figure 1, which shows the cyclical behaviour of the unemployment-vacancy relationship. The canonical labour market Diamond-Mortensen-Pissarides model describes this cyclical relationship as primarily from changes in vacancy creation in the search and matching process between the unemployed and unfilled vacancies (Elsby et al., 2015). Second, a rightward shift in the relationship can indicate that the labour market matching process has become less efficient. These shifts have typically occurred during recoveries in the United States since 1950, including during the recovery from the Great Recession, as shown by the data after August, 2009 in Figure 1 (Diamond & Şahin, 2015). Policymakers closely studied the causes of the Great Recession shift in the Beveridge curve since the longer-lasting potential causes helped them understand the sluggish labour market recovery from the Great Recession (Federal Open Market Committee, 2013).

Figure 1: National Beveridge curve 2000-2009 and Great Recession shift



Source*:* Author's estimates

State-level differences in the severity of the Great Recession can help inform about the potential causes of the Great Recession shift in the Beveridge curve. For example, Holmes & Otero (2020) examine pairwise Beveridge curves between states and find that housing and labour force participation differences across states helped reduce matching efficiency and contributed to shifts. This paper focuses on the Beveridge curves of individual states by decomposing the national Beveridge curve by state and constructing a novel benchmark to help identify states that contribute more or less than expected compared to the benchmark shift. The state excess shifts in their Beveridge curves are closely related to differences in states' relative labour market weakness during the aftermath of the Great Recession. States in the Southwest, Southeast, and Mid-Atlantic generally account for more of the shift than the benchmark, while states in the Great Plains, Great Lakes, and northern New England account for relatively less. Regression evidence based on the excess shifts suggests states that were more urbanized, were growing faster before the Great Recession, had relatively more workers in construction and natural resource extraction, and had higher house price appreciation between 2000 and 2006 contributed more to the outward shift in the Beveridge curve. Using a Quant likelihood ratio test to detect a structural break in each state's Beveridge curve, the timing of each state's shift around the Great Recession is examined. Thirty-five states and the District of Columbia had a breakpoint between November, 2009 and March, 2010. The remaining states mostly shifted in early 2007 or 2011, and there were few regional patterns in the timing of the shifts.

1. Literature Review

This paper is related to the literature on the Beveridge curve in three ways. First, it contributes to studying the Great Recession shift in the Beveridge curve. Beyond acknowledging the importance of long-term unemployment, there is little agreement on a single cause of a shift in the national Beveridge curve during the Great Recession since there are many potential causes of increased labour market matching inefficiency. Potential causes include more generous unemployment insurance (Bova et al., 2018), reduced worker mobility from housing market problems (Karahan & Rhee, 2019 and Holmes & Otero, 2020), skills mismatch (Şahin et al., 2014), uncertainty (Leduc & Liu, 2016), and diminished firm recruiting intensity (Davis et al., 2013). The diverse findings of the literature suggest complex causes of the shift. The state-level shifts are explored to help show the complex potential causes.

Second, it extends the Beveridge curve decomposition method of Ghayad & Dickens (2012) by creating benchmark shifts for each state and allowing for heterogeneous timing of the shifts. While Ghayad and Dickens' (2012) and Ghayad (2013) decompose the US Beveridge curve during the Great Recession by age, education, industry, and reason for unemployment, this paper focuses on a decomposition by state. States with large excess shifts show their labour market weakness as their relative share of the national unemployed increases. The flexible decomposition method is also compatible with different functional forms of the Beveridge curve, benchmarks, and methods to estimate breakpoints, and it can be used, even when local data on vacancies is unavailable. The benchmark methodology would help researchers and policymakers decompose shifts in the Beveridge curve by other categories, such as by sector or demographic groups, to highlight how different groups or sectors perform relative to each other after a shift in the Beveridge curve.

Third, the decomposition method can help the study of subnational Beveridge curves. Some past studies have focused on the long-term Beveridge curves of states, regions, and provinces, such as in Canada (Samson, 1994 and McPherson & Flores, 2012), Australia (Dixon et al., 2014), Germany (Kosfeld et al., 2008), Romania (Lincaru, 2010), and the United Kingdom (Wall & Zoega, 2002).

Other studies have focused on short-term shifts in the Beveridge curve from events, including for the Great Recession (Holmes & Otero, 2020) and the COVID-19 pandemic in the United States (Kindberg-Hanlon & Girard, 2024; Figura & Waller, 2024), for the influx of Syrian refugees in Turkey (Begen et al., 2023), for labour market reforms in Italy (Altavilla & Caroleo, 2013 and Destefanis & Fonseca, 2007), for a post-Great Recession shift in Austria (Böheim & Christl, 2022), and for a period of high unemployment in the Slovak Republic (Nota, 2008). Studies have also sought to compare Beveridge curves of regions or groups of countries with area-wide policymaking in mind, such as and Gökten et al. (2024) for the European Union and Destefanis et al. (2023) for the OECD.

This study extends decomposition methods used to study subnational Beveridge curves by showing how the decomposition with benchmarks can be used to show unexpected relative changes in state labour market trends and how those changes relate to the causes of the shifts of the Beveridge curve. Policymakers can use the results to find areas of unexpected labour market weakness relative to historical state (or region) trends that changes in the unemployment rate alone cannot illustrate. Since the timing of the shifts can differ by state, identifying the causes of a regional shift before it spills over can also help policymakers contain problems before they spill over.

Below, Section 2 details the Beveridge curve equation methodology and data. Section 3 discusses the shift results and the causes of the shifts. Section 4 explores extensions and robustness checks to the decomposition methodology.

2. Research Methodology

This section describes the model that builds the Beveridge curve for the decomposition. There are four steps to the decomposition. First, an equation that describes the Beveridge curve relationship between vacancies and unemployment is derived. Second, the Beveridge curve is estimated, the timing of a breakpoint, if any, is determined for each state, and the stable relationship between vacancies and unemployment before the breakpoint is re-estimated. Third, the actual unemployment in each state is compared to that predicted by the Beveridge curve after the break, which gives the increase in unemployment controlling for vacancies termed the shift in the Beveridge curve. Finally, a benchmark for how much increased unemployment would be expected in each state is calculated to determine whether each state accounts for more or less of the overall shift in the Beveridge curve than expected. The first step is discussed in Section 2.1, the remaining steps are discussed in Section 2.2, and the unemployment and vacancy data are discussed in Section 2.3.

2.1. Derivation of the Beveridge Curve

A regression equation that describes a convex, downward-sloping Beveridge Curve relationship between vacancies and unemployment can be derived from an extension of the continuous time labour market model of Blanchard & Diamond (1989) as modified by Dickens (2009). The Dickens (2009) model is modified to derive the Beveridge curve regression equation that is the basis for the decompositions below.

The model economy focuses on a continuum of firms' decisions to enter and operate facing uncertainty about their profits, a shock affecting their price, and irreversible capital purchase decisions. In this economy, each firm needs to hire a single worker to operate and knows their log real cost of production, w. Firm j's nominal log price at time t is $p_{j,t}$ and can be decomposed as follows:

$$p_{j,t} = p_t + z_{j,t}, \tag{1}$$

where: p_t denotes the natural log of the aggregate price level. The real price that each firm can charge, $z_{j,t}$, is a firm-specific shock that changes in jumps at rate c and follows a uniform distribution:

$$z_{j,t} \sim U(a,b)$$

$$a < w < 0 < b, \qquad b - a = 1.$$

The aggregate price level p_t is the geometric average of all firms' prices and is unobserved by individual firms. Firms cannot observe p_t, so they formulate a common guess for the aggregate price level p_t^e such that e_t is the error in their perception: $e_t = p_t - p_t^e$. While the shock changes infrequently, the aggregate price level is always changing as shocks arrive at other firms and affect their entry and exit decisions.

New firms decide to enter and produce and existing firms decide to produce based on p_t^e. Firms produce so long as perceived markup exceeds the real cost of production:

$$p_{j,t} - p_t^e > w.$$

New potential firms are created at rate s and must decide if they will enter and hire, and existing firms must decide if they will continue operating when they receive a new shock and price. Since new entrants and existing firms face the same profitability problem, they have the same decision rule. Define F_t as the fraction of new potential firms that hire and the fraction of existing firms receiving a new shock that continue operating. It follows that a fraction $1 - F_t$ of new potential firms decline to enter, while $1 - F_t$ of existing firms with a new shock exit.

The unemployed match with vacancies following a standard[1] Cobb-Douglas matching function:

$$M(U_t, V_t) = A V_t^q U_t^{1-q}. \tag{2}$$

The matching function depends on the number of unemployed U_t, vacancies V_t and the efficiency of the matching process A, and $0 < q < 1$. Changes in vacancies are described by their equations of motion:

$$dV_t = sF_t - c(1 - F_t)V_t - M(U_t, V_t). \tag{3}$$

The rate at which vacancies are created when entering firms decide to post a vacancy is sF_t. Vacancies are eliminated when newly created firms that have yet to fill their vacancy receive a new price that causes them to exit ($c(1 - F_t)V_t$) or a vacancy is filled ($M(U_t, V_t)$). Changes in unemployment are described by its equation of motion:

$$dU_t = c(1 - F_t)(L_t - U_t) - M(U_t, V_t), \tag{4}$$

[1] See Petrongolo & Pissarides (2001) for a discussion of this type of matching function.

where L_t is the labour force at time t. Firms' layoff their worker when they receive a new price that forces exit $(c(1-F_t)(L_t-U_t))$, and unemployed workers find a job when matched $(M(U_t,V_t))$.

The long-run equilibrium of the model is defined by the values of V_t and U_t when $e_t=0$, $dV_t=0$, and $dU_t=0$. Further, the number of potential firms created sF_t should equal the number of firms destroyed. The number of firms destroyed at each instant D_t is:

$$D_t=c(1-F_t)(V_t+L_t-U_t).$$

Define J_t as the number of existing and potential firms ($J_t=V_t+L_t-U_t$), and define $g_t=\frac{1-F_t}{F_t}$. The number of jobs destroyed becomes:

$$D_t=cg_tJ_tF_t.$$

In the long-run equilibrium, if potential firms created equals firms destroyed ($sF^*=D^*$ where variables with an asterisk are at their long-run equilibrium value):

$$sF^*=cg^*J^*F^*$$

$$s=cg^*J^*. \tag{5}$$

Equation (5) allows a restatement of the law of motion of vacancies (3) to:

$$dV_t=cg^*J^*F_t-c(1-F_t)V_t-M(U_t,V_t). \tag{6}$$

In the long-run equilibrium where $dV_t=0$ and $dU_t=0$, F_t can be solved out of (4) and (6), which leads to:

$$(1-u_t)=\left[1+\frac{j_t}{g^*j^*}\right]\frac{M(u_t,v_t)}{c} \tag{7}$$

Here, real variables in their lower-case values are the original variables denoted in upper case divided by the labour force L_t.

Taking the natural logarithm of both sides of (7) and using (2) yields:

$$ln\left(\frac{1-u_t}{u_t}\right)=ln\left(\frac{A}{c}\right)+qln\left(\frac{v_t}{u_t}\right)+ln\left(1+\frac{j_t}{g^*j^*}\right)$$

Treating the first term and the mean of the third term of the right-hand side of the equation as the constant of a regression and the remaining part of the third as the residual yields a regression estimation equation of a downward-sloping Beveridge curve:

$$\ln\left(\frac{1-u_t}{u_t}\right)=\beta_1+\beta_2\ln\left(\frac{v_t}{u_t}\right)+\epsilon_t \tag{8}$$

$$t=T_0,\ldots,T_{1,i}$$

Equation (8) fits a nonlinear relationship between vacancies and unemployment like that shown for the national data in Figure 1, and the paper uses a state-level version of this equation in the decomposition of the Beveridge curve in Section 2.2. As can be shown by rearranging this equation for vacancies in terms of unemployment as in (10) below, a traditional downward-sloping and convex Beveridge curve relationship between vacancies and unemployment results for $0<u<1$ when $0<\beta_2<1$.

2.2. Decomposing the Beveridge Curve

The strategy for the decomposition and estimating the breakpoints and shifts in Beveridge curve by state builds from Ghayad & Dickens (2012) and Ghayad (2013). The Beveridge curve relationship for each state between the aggregate vacancy rate (v_t) and state unemployed as a fraction of the national labour force in time t $(u_{i,t})$ is estimated using a modified version of (8) that allows unemployment to differ by state (i):

$$\ln\left(\frac{1-u_{i,t}}{u_{i,t}}\right) = \beta_{1,i} + \beta_{2,i}\ln\left(\frac{v_t}{u_{i,t}}\right) + \epsilon_{i,t} \tag{9}$$

The aggregate vacancy rate v_t is national vacancies divided by the national labour force. While state-level vacancy rate data is available, the national vacancy rate data allows for the national Beveridge curve to be broken down into the state-level components. These state-level Beveridge curve shifts highlight how state labour markets respond to national trends. Our decomposition is by state, while the previous literature considered demographic characteristics, sectors, and reasons for unemployment.

While the previous decompositions in Ghayad & Dickens (2012) and Ghayad (2013) use a fixed, chosen date for a breakpoint, we estimate a breakpoint for each state. The first period in the data is T_0, and the breakpoint for the Beveridge curve shift for state i is $T_{1,i}$ after which the Beveridge curve shifts. We estimate the timing of the shifts by state using a Quandt (1960) likelihood ratio test, which searches for a single breakpoint in a window of dates between January 2007 and December 2012. The test finds the best breakpoint candidate as the date with the maximum Chow (1960) test statistic across all possible breakpoints $T_{1,i}$ in the window and tests for significance of the break.

After re-estimating the Beveridge curves using data up to each state's breakpoint $T_{1,i}$, we compute the horizontal shift in the Beveridge curve state by state for the date of the shift $T_{1,i}+1$ and each subsequent month after the shift to T_2, which is the last month of the data for the post-shift period $(t = T_{1,i}+1, \ldots, T_2)$. This computation requires finding the unemployment in each state $(\hat{u}_{i,t})$ consistent with the national vacancy rate at that time. Rearranging (9) allows the vacancy rate to be expressed in terms of the expected unemployment rate from the Beveridge curve relationship:

$$v_t = \left(\frac{\hat{u}_{i,t}^{\beta_{2,i}-1} - \hat{u}_{i,t}^{\beta_{2,i}}}{e^{\beta_{1,i}}}\right)^{\frac{1}{\beta_{2,i}}}. \tag{10}$$

A Newton-Raphson root-finding algorithm allows the calculation of $\hat{u}_{i,t}$ consistent with (10) for each i and t using parameter estimates $\widehat{\beta_{1,i}}$ and $\widehat{\beta_{2,i}}$ in place of $\beta_{1,i}$ and $\beta_{2,i}$.

The shift in the Beveridge curve at each state and time $(s_{i,t})$ is the difference between the actual and predicted unemployment using (10):

$$s_{i,t} = u_{i,t} - \hat{u}_{i,t}. \tag{11}$$

The units of unemployment $u_{i,t}$ are relative to the national labour force, so the sum of $u_{i,t}$ across states is the national unemployment rate. Further, $s_{i,t}$ can be thought of as state i's contribution to the national Beveridge curve shift at time t. A positive value of $s_{i,t}$ indicates higher unemployment above what is consistent with the vacancy-unemployment relationship before the shift in the Beveridge curve, and a negative value indicates lower unemployment.

We define a benchmark for the expected Beveridge curve shifts by state to aid in comparing small and large states' shifts. Comparing the actual to benchmark shifts by state helps identify states with relatively worse or better labour market experiences during and after the Great Recession, controlling for the size of the states. First, we calculate π_i as state i's mean value of $u_{i,t}$ between the initial time of the data (T_0) and the first possible breakpoint (T^*: December 2006) for each state.

$$\pi_i = \frac{1}{T^* - T_0 + 1} \sum_{t=T_0}^{T^*} \left[\frac{u_{i,t}}{\sum_{l=1}^{N} u_{l,t}} \right] \qquad (12)$$

This state share π_i is equivalent to state i's mean share of the national unemployed over the period $t = T_0, \ldots, T^*$, and N is the number of states included in the analysis. The benchmark predicted shift in the Beveridge curve for state i, $\widehat{s_{i,t}}$, is the state share multiplied by the total shift in the Beveridge curve across states at time t:

$$\widehat{s_{i,t}} = \pi_i * \sum_{l=1}^{N} s_{l,t}. \qquad (13)$$

We express the states' excess Beveridge curve shifts in the results as the percentage difference relative to the expected shift:

$$s_{i,t}^{e} = \frac{s_{i,t} - \widehat{s_{i,t}}}{\widehat{s_{i,t}}} * 100. \qquad (14)$$

This unemployment-based benchmark will highlight states with weak recoveries from the Great Recession. In the results below, the excess shifts of states are highly correlated with changes in their share of the national unemployed. If a state has a larger Beveridge curve shift than its benchmark (a positive excess shift), then its relative share of unemployed nationally is increasing, which indicates a relatively weak labour market in that state, and vice versa. States with weak recoveries from the Great Recession may see increases in or stagnating unemployment compared to other states. Section 3.3 shows robustness checks for alternative benchmarks, including the labour force.

While the decomposition method focuses on the state Beveridge curves in the United States, it could be applied to study recessions and events in other nations or broken down by demographic group. The method relies on the existence a Beveridge curve relationship between the area-wide job vacancy rate (here, national) and the regions' unemployment (states). It could be used to study shifts in local labour markets within a state following events and reforms where there is a Beveridge curve-like relationship between county unemployment and state job vacancies even without county-level vacancy data. Caution should be used when the regional labour markets exhibit substantial heterogeneity and do not follow a common trend or when there are insufficient observations between structural breaks to establish a stable, baseline Beveridge curve. For example, the method may not give reliable results in a decomposition of OECD countries where some members' labour markets do not follow international trends. Care should then be taken to ensure that there is a Beveridge curve relationship between area-wide vacancies and regional unemployment in applications where the strength and stability of this relationship is not clear, such as applications to the European Union.

2.3. Data

The decomposition uses monthly data from three sources. Vacancy data is from the Job Opening and Labour Turnover Survey (JOLTS). State unemployment data is from the Local Area Unemployment Statistics of the Bureau of Labor Statistics (BLS). Labour force data comes from the Current Employment Statistics program of the BLS. The data is from December 2000 to December 2017. The start of the sample is constrained by data availability from JOLTS. All 50 states and the District of Columbia are included in the sample, so $N = 51$.

3. Research Results

The state Beveridge curve results after accounting for the breakpoints in Table 1 show the expected negative relationship between vacancies and unemployment since $0 < \beta_{2,i} < 1$ for all states.

Table 1: State Beveridge curve estimation results

State/District	$\widehat{\beta_1}, se(\widehat{\beta_1})$	$\widehat{\beta_2}, se(\widehat{\beta_2})$	State/District	$\widehat{\beta_1}, se(\widehat{\beta_1})$	$\widehat{\beta_2}, se(\widehat{\beta_2})$
Alaska	7, (0,09)	0,34, (0,02)	Montana	6,2, (0,07)	0,51, (0,01)
Alabama	5,22, (0,03)	0,56, (0,01)	North Carolina	4,85, (0,02)	0,56, (0,01)
Arkansas	5,97, (0,04)	0,42, (0,01)	North Dakota	7,69, (0,06)	0,3, (0,01)
Arizona	5,03, (0,03)	0,58, (0,01)	Nebraska	6,43, (0,06)	0,41, (0,01)
California	4,19, (0,01)	0,57, (0,01)	New Hampshire	6,08, (0,04)	0,51, (0,01)
Colorado	5,11, (0,03)	0,57, (0,01)	New Jersey	4,94, (0,02)	0,55, (0,01)
Connecticut	5,2, (0,05)	0,6, (0,01)	New Mexico	5,93, (0,07)	0,49, (0,02)
District of Columbia	6,58, (0,06)	0,44, (0,01)	Nevada	5,12, (0,06)	0,64, (0,01)
Delaware	6,85, (0,11)	0,41, (0,02)	New York	4,58, (0,02)	0,54, (0,01)
Florida	4,49, (0,02)	0,62, (0,01)	Ohio	4,84, (0,03)	0,5, (0,01)
Georgia	4,81, (0,04)	0,59, (0,01)	Oklahoma	5,54, (0,08)	0,52, (0,02)
Hawaii	5,69, (0,07)	0,6, (0,01)	Oregon	5,26, (0,03)	0,53, (0,01)
Iowa	5,81, (0,04)	0,47, (0,01)	Pennsylvania	5,02, (0,02)	0,44, (0,01)
Idaho	5,45, (0,05)	0,62, (0,01)	Rhode Island	5,66, (0,07)	0,58, (0,01)
Illinois	4,79, (0,02)	0,51, (0,01)	South Carolina	5,25, (0,05)	0,52, (0,01)
Indiana	5,07, (0,03)	0,55, (0,01)	South Dakota	6,92, (0,07)	0,42, (0,01)
Kansas	5,85, (0,04)	0,45, (0,01)	Tennessee	5,06, (0,04)	0,55, (0,01)
Kentucky	5,99, (0,07)	0,34, (0,02)	Texas	4,58, (0,02)	0,49, (0,01)
Louisiana	4,77, (0,11)	0,68, (0,03)	Utah	5,09, (0,04)	0,66, (0,01)
Massachusetts	5,16, (0,02)	0,52, (0,01)	Virginia	5,1, (0,02)	0,56, (0,01)
Maryland	5,36, (0,04)	0,5, (0,01)	Vermont	6,83, (0,12)	0,44, (0,02)
Maine	5,97, (0,06)	0,51, (0,01)	Washington	5,13, (0,04)	0,51, (0,01)
Michigan	5, (0,07)	0,45, (0,03)	Wisconsin	5,26, (0,03)	0,5, (0,01)
Minnesota	5,64, (0,05)	0,42, (0,01)	West Virginia	6,08, (0,08)	0,46, (0,02)
Missouri	5,29, (0,03)	0,48, (0,01)	Wyoming	6,51, (0,1)	0,52, (0,02)
Mississippi	5,97, (0,08)	0,39, (0,02)			

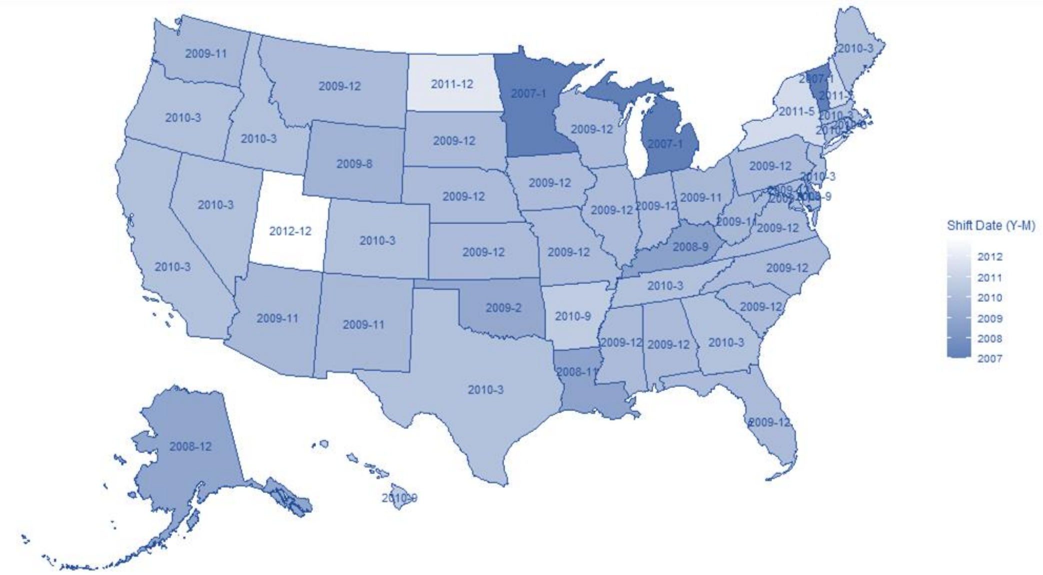
Source: Author's estimates

The timing of breakpoints and size of excess shifts in the Beveridge curve across states are presented in Section 3.1. The economic and demographic factors related to the shifts are explored in Section 3.2.

3.1. State Beveridge Curve Shifts

While most states had Beveridge curve shifts in 2009 and 2010, differences between state and national unemployment trends explain early or late state shifts. Thirty-five states and the District of Columbia experienced a Beveridge curve shift between November, 2009 and March, 2010 as shown by the baseline results in Figure 2 and Table 2 column 2[2].

Figure 2: Timing of the shifts of the Beveridge curve, baseline results



Source*:* Author's estimates

Table 2: Baseline results, benchmark and functional form robustness

State/District	Baseline Results		2006 Benchmark	Labour Force Benchmark	Logarithm Functional Form	
	Excess Shift (%)	Shift Date (Y-M)	Excess Shift (%)	Excess Shift (%)	Excess Shift (%)	Shift Date (Y-M)
	(1)	(2)	(3)	(4)	(5)	(6)
Alaska	-78	2008-12	-80,1	-71,2	-76,6	2009-2
Alabama	24,8	2009-12	45,9	24,8	20,8	2009-12
Arkansas	-77,8	2010-9	-80,7	-78,2	-68,8	2010-9
Arizona	86,9	2009-11	88,8	81,1	76,4	2009-12
California	29,1	2010-3	40,4	46,3	25,1	2010-3
Colorado	-26,1	2010-3	-23,5	-28,6	-23,2	2010-9
Connecticut	86,9	2010-3	62,6	54,8	86,7	2010-9
District of Columbia	20	2009-11	19,4	49,5	25,5	2010-9
Delaware	74,8	2008-9	63,9	28,7	69,5	2009-12
Florida	107,9	2009-12	146,6	84	99,3	2010-3
Georgia	99,6	2010-3	68,4	74,7	99,4	2010-9
Hawaii	5,1	2010-9	27,7	-28,4	9,2	2010-9
Iowa	-62,9	2009-12	-64,3	-71,9	-62,3	2010-3

[2] The mean calculation start date of January 2010 is when a majority of states have shifted, which avoids overestimating the importance of states that shifted relatively early.

State/District	Baseline Results		2006 Benchmark	Labour Force Benchmark	Logarithm Functional Form	
	Excess Shift (%)	Shift Date (Y-M)	Excess Shift (%)	Excess Shift (%)	Excess Shift (%)	Shift Date (Y-M)
	(1)	(2)	(3)	(4)	(5)	(6)
Idaho	8,9	2010-3	35	1,6	8,7	2010-9
Illinois	-6,5	2009-12	7,5	5,7	-7,7	2009-12
Indiana	-21,5	2009-12	-31,6	-27	-20,2	2010-3
Kansas	-85	2009-12	-84,9	-85,8	-82,1	2010-3
Kentucky	-36,2	2008-9	-45,7	-33,1	-27,6	2009-12
Louisiana	-29,7	2008-11	-7,2	-21	56,1	2012-12
Massachusetts	-27,8	2010-3	-33,2	-34,6	-30,1	2010-3
Maryland	47,2	2009-12	40,5	17,3	43	2010-3
Maine	-37,2	2010-3	-47,5	-47,3	-29,6	2010-9
Michigan	-74,7	2007-1	-79	-70,1	-65,5	2007-1
Minnesota	-52,2	2007-1	-55	-61,8	-48,9	2007-1
Missouri	-52,8	2009-12	-54,8	-53,4	-49,1	2009-12
Mississippi	-51,9	2009-12	-56,9	-43,9	-35,5	2010-9
Montana	-11,5	2009-12	0,5	-26	-14	2009-12
North Carolina	18,1	2009-12	21,8	26,1	15,2	2010-3
North Dakota	-92,3	2011-12	-93,2	-95,3	-77,3	2012-12
Nebraska	-77,1	2009-12	-76	-84,5	-78,7	2008-12
New Hampshire	-48,5	2011-5	-50,4	-62,5	-46,7	2011-5
New Jersey	51,5	2010-3	40,8	40,6	46,2	2010-3
New Mexico	41,6	2009-11	54,9	42,2	61,8	2011-8
Nevada	215,1	2010-3	193,8	186,1	203,5	2010-3
New York	-4,5	2011-5	4	-0,4	-7,8	2011-5
Ohio	-60,6	2009-11	-64	-58,5	-59,1	2009-12
Oklahoma	-29,5	2009-2	-29,1	-41,2	-37,8	2009-2
Oregon	-60,8	2010-3	-55,4	-48,9	-59,1	2010-3
Pennsylvania	-20,2	2009-12	-22,2	-22,3	-23	2010-3
Rhode Island	56,2	2010-3	30,2	46,5	58,9	2010-9
South Carolina	-37,7	2009-12	-49	-27,5	-34,2	2010-3
South Dakota	-49,4	2009-12	-51	-68,6	-43,8	2010-3
Tennessee	-3,3	2010-3	-17,9	-7,1	-0,7	2010-9
Texas	-26,5	2010-3	-26,2	-19,9	-27,5	2010-3
Utah	5,8	2012-12	48,7	-3,7	2,6	2012-12
Virginia	65,4	2009-12	67,8	13,8	55,3	2009-12
Vermont	-60,7	2007-1	-65,7	-72,9	-54,1	2007-1
Washington	-22,7	2009-11	-16,1	-7,8	-22,9	2009-12
Wisconsin	-59,5	2009-12	-62,1	-62,6	-56,4	2011-5

State/District	Baseline Results		2006 Benchmark	Labour Force Benchmark	Logarithm Functional Form	
	Excess Shift (%)	Shift Date (Y-M)	Excess Shift (%)	Excess Shift (%)	Excess Shift (%)	Shift Date (Y-M)
	(1)	(2)	(3)	(4)	(5)	(6)
West Virginia	-15,5	2009-11	-13,5	-12,7	-9,3	2010-9
Wyoming	57,3	2009-8	70,4	14,7	53,9	2009-11
Mean Abs. Change	-	-	12,6	9,9	6,5	4,8 m.
Corr. with Baseline	-	-	0,973	0,966	0,976	

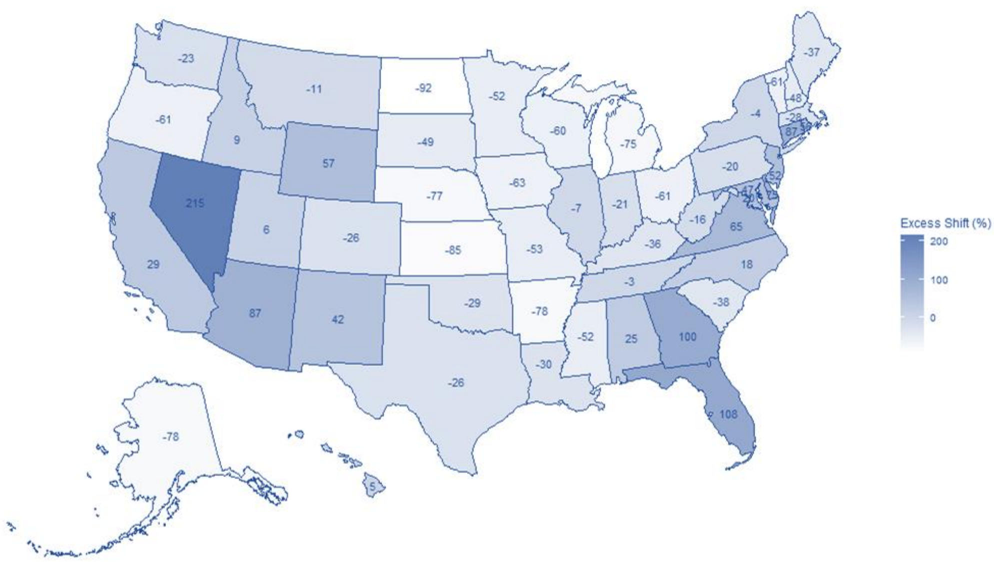
Source*:* Author's estimates

The earliest and latest shifting states have unemployment rate trends that differ from the national rate, which started a rapid increase in November, 2007 from 4,7% to a peak of 10% in October 2010 and then slowly fell. The earliest shifting states in 2007, Michigan, Minnesota, and Vermont, each had rising unemployment in 2007 and state-level recessions in 2006 according to state business cycle dating by Flora (2016). Among the latest shifting states from late 2010, Arkansas, Hawaii, New Hampshire, and New York had prolonged or secondary peaks in their unemployment in 2011 and 2012.

With the breakpoints in hand, the excess shifts and how they relate to the state changes in unemployment are studied. Since the state Beveridge curves estimates rely on the national vacancy rate, their expected unemployment changes after the shift represent how state unemployment is expected to respond to national labour demand conditions. The shifts are the gaps between the actual and expected unemployment shares from the states, and the excess shifts are the mean percentage changes in the shift compared to the benchmark shift, which represent the relative recovery of each state from the Great Recession. Policymakers can use the excess shifts to identify areas of unexpected labour market weakness given historical trends to identify areas that would benefit from stimulus programs, such as job training and workforce development, small business support, and allocations for infrastructure programs. Below, the states' unexpected labour market weakness, the excess shifts, are connected to commonly cited causes of the Great Recession and other economic factors.

There is substantial cross-sectional variation in the size of Beveridge curve shifts. Figure 3 and Table 2, column 1 show the mean excess percentage shift in the Beveridge curve by state $\bar{s_i^e}$ between January, 2010 and December, 2017.

Figure 3: Mean excess shifts of the Beveridge curve (%), baseline results



Source*:* Author's estimates

States with a positive percentage in Figure 3 are states with a shift larger than the benchmark shift, and states between 0 and -100% have a smaller shift than the benchmark. States with a shift less than -100% would contribute toward an inward shift in the national Beveridge curve. North Dakota, with the fastest three-year job recovery and earliest trough among all states during its relatively mild Great Recession experience, had nearly no shift with a -92,3% excess shift (Walden, 2014). Fourteen states had shifts that were less than half of their benchmark with an excess shift less than -50%. On the other hand, Nevada accounted for more than triple its expected shift with a 215,1% excess shift. Clinger & Rodgers (2010) and Parker & Marshall (2017) note that Nevada faced an exceptionally severe Great Recession experience because of rapid decreases in housing prices and a fiscal crisis from rapid declines in sales and gaming tax revenue. While the timing of the Beveridge curve shifts shows few systematic regional differences, there are regional patterns in the excess shifts. States in the Southwest, Southeast, and the Mid-Atlantic include most states with a larger shift than the expected benchmark. In contrast, states in the Great Plains, the Great Lakes, Northern New England, and the Pacific Northwest saw smaller shifts than the benchmark.

3.2. What Explains the Excess Beveridge Curve Shifts?

To examine what affects states' relative labour market performance after the Great Recession, we estimate a cross-sectional regression that relates the states' mean excess shifts to potential causes and exacerbating factors of the Great Recession, and state economic and demographic factors. We estimate the effects of the factors on $\bar{s_i^e}$, which is the mean excess state shift between January, 2010 and December, 2017, by estimating:

$$\bar{s_i^e} = \alpha + \beta X_i + e_i \tag{15}$$

where the vector of regressors X_i include the factors that relate to the causes of the shifts[3].

We note that in applications to other geographies and from different events that the choice of the regressors will depend on the potential causes of shifts and the characteristics of the events and areas studied. We include the house price appreciation rate between 2000 and 2006 as a regressor to explore how volatile housing markets contributed to later labour market problems as supported by Karahan & Rhee (2019). Following Glaeser et al. (2008), which finds urban areas are more prone to housing market volatility than rural areas because of a more inelastic supply of homes, we include the urbanization rate[4]. We also include region dummies to help control for region-specific factors and geographic mismatch, sectoral employment shares to detect higher unemployment because of skills mismatch as supported by Şahin et al. (2014), and the population growth rate as an additional demographic factor[5].

The regression does not include regressors from the post-shift period to avoid concerns about simultaneity and to ensure that policymakers can study the excess shifts with information available prior to the shifts, though they could be studied through the dynamics of the excess shifts in future research. The results in column 1 of Table 3 suggest excess shifts depend significantly on a variety of factors[6].

[3] We choose the end date for the study of the shift (T_2) as December 2017 since the national Beveridge curve had shifted nearly back to its pre-Great Recession level by that time, as noted in Lubik (2021).

[4] The urbanization rate is the state urbanization rate reported from the 2000 Census.

[5] Population growth (2000–2006) is from Census State Intercensal Tables; house price appreciation (Q4 2000–Q4 2006) from the Federal Housing Administration; and sectoral employment shares (Dec 2000–Dec 2006) from BLS Current Employment Statistics.

[6] The West region and the government employment share dummies are omitted from the regression, so the parameter estimates for the region dummies are relative to the West region, and the employment share parameter estimates are relative to government sector employment.

Table 3: Regression results for factors related to the excess shifts

Independent Variables	Baseline	Alt. Causes	Housing Int.	Industries
	(1)	(2)	(3)	(4)
Population Growth Rate (%/year)	35,125***	29,603*	35,776***	31,004***
	(12,255)	(15,682)	(12,419)	(11,362)
Urbanization Rate (%)	1,301***	1,019	1,177**	0,931
	(0,492)	(0,845)	(0,592)	(0,625)
House Price Appreciation Rate (%/year)	6,152**	6,932**	7,643***	5,076*
	(2,830)	(3,428)	(2,386)	(2,769)
Private Service Share (%)	1,233	1,148	1,380	
	(2,071)	(2,122)	(2,366)	
Manufacturing Share (%)	1,203	0,918	0,514	-0,151
	(2,203)	(2,310)	(2,666)	(2,003)
Construction and Resource Share (%)	10,835***	11,310***	10,517***	8,279***
	(2,850)	(3,194)	(3,068)	(2,843)
Midwest	34,295	28,875	75,899*	30,453
	(21,055)	(22,551)	(44,730)	(25,198)
Northeast	59,914**	56,627*	-30,278	79,375**
	(29,835)	(33,302)	(88,066)	(32,197)
South	57,893***	44,943	83,791*	45,484*
	(19,035)	(30,286)	(50,779)	(24,176)
Recipiency Rate (%)		-0,315		
		(0,750)		
Small Bus. Share (%)		-1,247		
		(2,359)		
Midwest*Housing Appreciation			-6,558	
			(5,236)	
Northeast*Housing Appreciation			9,501	
			(6,425)	
South*Housing Appreciation			-2,803	
			(3,997)	
Trade, Trans., and Util.				-3,823
				(3,595)
Information				-16,778*
				(9,536)
Financial Activities				7,824
				(5,303)
Prof. and Bus. Services				1,165
				(3,044)
Education and Health Services				-6,122

Independent Variables	Baseline	Alt. Causes	Housing Int.	Industries
	(1)	(2)	(3)	(4)
				(4,599)
Other Services				-1,033
				(11,953)
Constant	-377,329***	-268,488	-385,174**	-90,966
	(143,629)	(231,927)	(154,066)	(128,241)
Adjusted R^2	0,668	0,655	0,661	0,677
Residual Std. Error	35,282 (df = 41)	35,929 (df = 39)	35,607 (df = 38)	34,768 (df = 36)
F Statistic	12,155***	9,638***	9,139***	8,491***

Note: Sample size is 51. White (1980) robust standard errors in parentheses, *p<0,1; **p<0,05; ***p<0,01.
Source*:* Author's estimates

The full results in column 1 suggest that population growth, urbanization, house price appreciation, and employment in the construction, natural resource, and mining super sectors are all associated with significant and higher excess shifts. These results suggest that skills mismatch and housing market issues were significant factors in states' relative labour market recovery after the Great Recession with some role for geographic mismatch. The higher excess shifts for states with more construction and natural resource employment are consistent with Şahin et al. (2011), which finds that construction sector employment losses were significantly higher than in other sectors and could be a significant driver of shifts in the Beveridge curve. While the Northeast and South regions have significant and higher shifts relative to the West region, geographic mismatch does not appear to be the primary cause of the Beveridge curve shifts. One reason is that small states would not account for a substantial change in national unemployment unless they account for several times more of a shift in the Beveridge curve than expected. While Nevada, with a 2010 Census population of 2,7 million, accounts for more than triple its benchmark shift, the national unemployment rate would only fall by about 0,03% if its unemployment was at its benchmark expected level. A shift caused by significant geographic mismatch would require differences in unemployment trends between populous states that would cause large inward and outward shifts in the Beveridge curve or significant differences in the timing of unemployment changes, neither of which are suggested by the baseline results.

We consider some alternative regression specifications to explore the robustness of the cross-sectional regression results about the excess shifts. First, the sensitivity of the results to additional factors that could explain shifts in the Beveridge curve is examined, and these factors are included in $\mathrm{X_i}$. The average recipiency rate of unemployment insurance benefits is included to control for state differences in unemployment insurance availability and use[7]. Also, the share of employment in a state by small businesses with fewer than 500 employees is used to control for the disproportionately negative impact of weak demand, uncertainty, and credit conditions on small businesses documented by Şahin et al. (2011)[8]. The results in column 2 of Table 3 include these additional factors. Neither of the added variables are significant, and parameter estimates are largely similar to the baseline. While population growth and the Northeast region become weakly significant, and the urbanization rate and the South region are no longer significant, examination of the variance inflation factors of the regression suggests imperfect multicollinearity related to the small business employment shares. Second, the regional dependence of the excess shifts on house price appreciation is examined using regional interaction effects, as Famiglietti et al. (2020) find significant regional differences in the severity and duration of the Great Recession related to housing market conditions.

[7] The recipiency rate data from the Department of Labor's Employment & Training Administration between 2000 - 2006 is used.
[8] Employment by firm size is available through the United States Census Bureau's Statistics of U.S. Businesses. The state share of small business employment averaged between 2000 and 2006 is used.

The results in column 3 of Table 3 show the results are robust, as interaction effects are not significant and other results are similar to the baseline. Third, the baseline sector groups are disaggregated to NAICS super sectors[9] to explore the excess shifts' dependence on different parts of the service sector. Results in column 4 of Table 3 show little change from the baseline results. Housing price appreciation is now significant at the 10% instead of the 5% level, and only information sector employment is weakly significant at the 10% level among the disaggregated sectors.

One limitation of the cross-sectional regression analysis is that it uses only information on the regressors prior to the shifts in the Beveridge curve to limit simultaneity and data availability concerns. Events and economic changes concurrent to the shift period affect the timing of the shifts and size of the initial excess shifts. However, events after the initial shifts occur, such as state labour market reforms, differences in the duration of unemployment insurance eligibility, or oil price shocks, could lead to higher unemployment rates in some states and larger excess shifts. In general, the effects of events and reforms during the post-shift period can be avoided by adjusting the end date of the post-shift study period, studied by examining their effects on the excess shifts, or studied more directly by studying shifts from these events if enough data is available prior to the shift to form a stable Beveridge curve. For example, a significant drop in oil prices in 2014, likely demand-driven as discussed in Alsalman (2023), contributed to higher unemployment in states with significant oil and gas production. Karaki (2018) documents that such oil price shocks likely increased unemployment in states with high oil and gas production but reduced it in some others. Higher unemployment in the most significantly affected states would cause their excess shifts to rise independently of the causes of the Great Recession shifts in the Beveridge curve. While this concern is mitigated in our results by the generally low excess shifts in oil-producing states, the decomposition could exclude this period by adjusting the end date of the post-shift study period T_2 to early 2014 or studying it separately to detect Beveridge curve shifts as oil prices decreased. However, this paper focuses on the effects of the Great Recession, so such work is left for future research.

4. Extensions and Robustness

In this section, extensions of the methodology to alternative functional forms and breakpoint estimation methods, and the robustness of the results to alternative benchmarks are explored.

4.1. Alternative Benchmarks

In this subsection, the robustness of the results to alternative calculations of the shift benchmarks are explored by calculating alternative state shares of the expected Beveridge curve shift π_i, which are the average share of national unemployment for the pre-shift period between December, 2000 and December, 2006 in the baseline. Changing benchmarks affects neither the Beveridge curve estimation nor the shift dates, so the shift dates are the same as the baseline for benchmark robustness checks. Generally, if the benchmark change causes a state's share π_i to increase, then its expected shift $\widehat{s_{i,t}}$ increases in (13), which decreases its excess shift in the Beveridge curve (14).

2006 Benchmark

An alternative benchmark is selected to address the possibility that the share of the unemployed may change over time across states because of migration, population growth, and demographics. The baseline state shares based on 6 years of data may underestimate faster-growing states' share of unemployed after 2006, so the alternative benchmark from just 2006 is computed, which is the last year before the possible shifts.

Table 2, column 3 shows the excess shifts with the benchmark shift set to be the states' share of unemployed averaged in 2006. This alternative specification is overall robust, with a 0,973 cross-sectional correlation between

[9] Some smaller states do not have separate data on the natural resource and mining supersector, so the construction, natural resource, and mining sectors are combined.

excess shifts of this benchmark and the baseline. For example, Nevada, with the fastest population growth between 2000 and 2010, still shows a Beveridge curve shift roughly triple the expected amount. Utah and Florida had their excess shifts increase by more than 35 percentage points in this benchmark due to low unemployment in 2006. Both states had unemployment rates below 3% in 2006, contributing to Florida's unemployed share dropping from 5,2% to 4,3%, and Utah's from 0,76% to 0,53% in this benchmark. These findings indicate that a short benchmark window is sensitive to temporary local economic changes.

The cross-sectional regression results from (15) with the new excess shifts $\bar{s_i^e}$ from the expected benchmark are shown in column 2 of Table 4.

Table 4: Cross sectional regression results for functional form robustness checks

Independent Variables	Baseline	2006 Benchmark	LF Benchmark	Log Form
	(1)	(2)	(3)	(4)
Population Growth Rate (%/year)	35,125***	28,336***	30,271**	21,243
	(12,255)	(10,458)	(12,270)	(14,821)
Urbanization Rate (%)	1,301***	1,313***	1,589***	1,251***
	(0,492)	(0,445)	(0,427)	(0,456)
House Price Appreciation Rate (%/year)	6,152**	6,790***	4,897**	5,669*
	(2,830)	(2,591)	(2,485)	(2,977)
Private Service Share (%)	1,233	1,549	-0,663	1,871
	(2,071)	(2,083)	(2,107)	(2,211)
Manufacturing Share (%)	1,203	1,425	1,002	1,386
	(2,203)	(2,256)	(2,101)	(2,383)
Construction and Resource Share (%)	10,835***	12,011***	6,545**	12,658***
	(2,850)	(2,271)	(3,019)	(3,506)
Midwest	34,295	20,723	15,629	24,205
	(21,055)	(20,573)	(21,010)	(20,935)
Northeast	59,914**	35,118	44,281	47,197
	(29,835)	(27,387)	(27,373)	(28,859)
South	57,893***	46,445**	45,188**	56,781***
	(19,035)	(18,563)	(17,579)	(18,968)
Constant	-377,329***	-395,048***	-227,220	-404,442**
	(143,629)	(148,502)	(150,021)	(169,235)
Adjusted R^2	0,668	0,694	0,630	0,606
Residual Std. Error (df = 41)	35,282	34,226	33,373	36,658
F Statistic (df = 9; 41)	12,155***	13,574***	10,471***	9,548***

Note: Sample size is 51. White (1980) robust standard errors in parentheses, *p<0,1; **p<0,05; ***p<0,01.
Source*:* Author's estimates

The results are largely robust, except that the Midwest and Northeast regions lose significance, though their parameter estimates are of the same sign as in the baseline results.

Labour Force Benchmark

The 2006 benchmark indicates the results can be sensitive to short-term trends. Thus, the state labour force shares are considered as a potentially more stable benchmark due to the relative stability of the labour force compared to unemployment. Table 2, column 4 shows the excess shifts if the benchmark uses each state's share of the labour force instead between December 2000 and December 2006, and they are closely related to the baseline excess shifts with a 0,966 correlation. West Coast states and the District of Columbia have higher excess shifts than the baseline since their average unemployment rates were higher than the national average between 2000 and 2006. Their shares of the Beveridge curve shift are lower under the labour force benchmark, which causes their excess shifts to be higher than the baseline. Likewise, states with falling excess shifts had lower unemployment rates between 2000 and 2006, higher expected shifts under a labour force benchmark, and lower excess shifts compared to the baseline.

The cross-sectional regression results from (15) with the labour force benchmark excess shifts are in the 4th column of Table 4. The population growth rate is now only significant at the 10% level, and the manufacturing share, Midwest region, and Northeast region lose significance, but the parameter estimates are still the same sign as in the baseline results. Overall, the labour force benchmark results appear to be a reasonable alternative benchmark, but the excess shifts are not as closely related to the change in the changes of the state unemployment shares before and after the shifts (correlation: 0,931).

4.2. Natural Logarithm Beveridge Curve Estimation

The baseline algorithm can be modified to incorporate simple, common alternative functional forms for the Beveridge curve between vacancies and unemployment, such as the natural logarithm functional form, which Michaillat & Saez (2021) argue is an appropriate functional form for the Beveridge curve. The Beveridge curve regression equation for the logarithm form is:

$$\ln(v_t) = \gamma_{1,i} + \gamma_{2,i}\ln\left(u_{i,t}\right) + \epsilon_{i,t} \tag{16}$$

An advantage of this specification is simplicity: it does not require the use of root-finding algorithms to find the predicted unemployment rate given the vacancy rate. The predicted unemployment rate at time t corresponding to (10) is:

$$\widehat{u_{i,t}} = \exp\left(\frac{\ln(v_t) - \gamma_{1,i}}{\gamma_{2,i}}\right) \tag{17}$$

There are no other changes to the baseline algorithm for computing the Beveridge curve shifts.

The natural logarithm functional form leads to minor changes compared to the baseline results, as shown in Table 2, columns 5 and 6. The correlation between the excess shifts in the benchmark and logarithm forms is high at 0,976. Compared to the baseline, the main difference is that the breakpoints are estimated slightly later on average, with 11 states and the District of Columbia shifting in September of 2010. Louisiana shifts in December, 2012, more than 4 years after the baseline shift, and has an 85.8% higher excess shift. As described in more detail below in Section 4.3., Louisiana experienced high unemployment after Hurricane Katrina, which makes Louisiana's expected unemployment from the Beveridge curve higher in a shorter sample than the baseline. The late shift, combined with its relatively higher unemployment starting in late 2014 compared to the national rate, cause Louisiana's excess shift to be positive (56,1%) rather than negative in the baseline. The cross-sectional regression results on the logarithm form's excess shifts in Table 4 column 4 are similar to the baseline results, except population growth is no longer significant, and house price appreciation is significant at the 10% instead of the 5% level. Both parameter estimates remain positive, and the parameter on house price appreciation is similar to the baseline.

4.3. Alternative Breakpoint Estimation

In the baseline, state breakpoints are chosen using a Quandt (1960) likelihood ratio test, which is a common test to find a single breakpoint at an unknown date. In this subsection, alternative breakpoint selection methods are evaluated to examine the robustness of the results to the breakpoints. The common breakpoints examine the use of the national breakpoint and later breakpoints as the state breakpoints. Multiple breakpoints may exist in the data, and the Bai & Perron (1998, 2003) method is employed to evaluate the potential for multiple breaks in the sample.

Common Breakpoints

The use of common breakpoints across states instead of state-specific breakpoints is explored in the estimation of (9). In the common breakpoint results, the excess Beveridge curve shifts are calculated starting immediately after the breakpoint. Two common breakpoints are used: August, 2009, which matches the aggregate shift in the Beveridge curve, and December, 2010, after most state Beveridge curves have shifted in the baseline results. First, column 3 of Table 5 shows the excess shift results if each state has the same August 2009 breakpoint as the national Beveridge curve.

Table 5: Excess shifts for alternative breakpoints extensions

State/District	Baseline Results		Aug. 2009 Breakpoint	Dec. 2010 Breakpoint	Bai-Perron Estimation		Bai-Perron Breakpoints
	Excess Shift (%)	Shift Date (Y-M)	Excess Shift (%)	Excess Shift (%)	Excess Shift (%)	Shift Date (Y-M)	Excess Shift (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alaska	-78	2008-12	-78,5	-79,6	-66,5	2009-8	-78,7
Alabama	24,8	2009-12	31	29,6	55,6	2007-5	31,8
Arkansas	-77,8	2010-9	-82,1	-82	-98,5	2009-1	-85,1
Arizona	86,9	2009-11	93,2	96,9	104,7	2009-11	95,6
California	29,1	2010-3	27,5	28,5	46	2007-2	32,6
Colorado	-26,1	2010-3	-24,1	-29,4	-13,8	2009-12	-25,7
Connecticut	86,9	2010-3	81,4	85,2	37,7	2007-5	90,4
District of Columbia	20	2009-11	28,9	30,5	41,6	2009-7	25,6
Delaware	74,8	2008-9	78	87,9	67,4	2009-11	81,5
Florida	107,9	2009-12	105,9	112	144,7	2007-2	119,7
Georgia	99,6	2010-3	87,8	96,8	46,2	2009-3	88,1
Hawaii	5,1	2010-9	6,7	5,2	36,9	2007-5	10,8
Iowa	-62,9	2009-12	-62,9	-62,9	-68,2	2008-11	-64,7
Idaho	8,9	2010-3	18,4	15,3	47,4	2009-3	17,7
Illinois	-6,5	2009-12	-5,4	-1,1	10	2007-2	-2
Indiana	-21,5	2009-12	-26,7	-24,3	-37,7	2009-11	-24,2
Kansas	-85	2009-12	-86,2	-87,8	-72,9	2009-4	-85,7
Kentucky	-36,2	2008-9	-36,3	-35,4	-54,7	2009-1	-40,1
Louisiana	-29,7	2008-11	8,9	3,3	-14,8	2007-9	-16,4
Massachusetts	-27,8	2010-3	-27	-25,2	-48,1	2007-3	-24,9
Maryland	47,2	2009-12	51,6	55,6	38,1	2007-3	34,5
Maine	-37,2	2010-3	-43,5	-40,8	-74,7	2009-1	-44,8

State/District	Baseline Results		Aug. 2009 Breakpoint	Dec. 2010 Breakpoint	Bai-Perron Estimation		Bai-Perron Breakpoints
	Excess Shift (%)	Shift Date (Y-M)	Excess Shift (%)	Excess Shift (%)	Excess Shift (%)	Shift Date (Y-M)	Excess Shift (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Michigan	-74,7	2007-1	-90,1	-87,1	-128,9	2009-1	-90
Minnesota	-52,2	2007-1	-63,5	-65,9	-98,8	2009-3	-62,7
Missouri	-52,8	2009-12	-58,4	-59,4	-68,2	2009-4	-57,5
Mississippi	-51,9	2009-12	-56,5	-55,8	-111,3	2007-5	-53,9
Montana	-11,5	2009-12	-4,8	-5,6	8,3	2007-5	-3,2
North Carolina	18,1	2009-12	19,1	18,3	24,8	2008-10	16,7
North Dakota	-92,3	2011-12	-93,6	-94,7	-113	2007-11	-96,7
Nebraska	-77,1	2009-12	-74,4	-77,2	-50,3	2009-7	-74,7
New Hampshire	-48,5	2011-5	-56,7	-49,3	-64,7	2007-4	-56
New Jersey	51,5	2010-3	52	56,1	46	2009-8	51,4
New Mexico	41,6	2009-11	67	65,3	36,6	2007-5	46,4
Nevada	215,1	2010-3	185,7	203,5	113,6	2009-11	191,3
New York	-4,5	2011-5	-5,9	-4	4,2	2009-8	-8,2
Ohio	-60,6	2009-11	-64,7	-66	-83,9	2009-11	-61,8
Oklahoma	-29,5	2009-2	-21,3	-22,3	-41,4	2007-12	-33,5
Oregon	-60,8	2010-3	-58,7	-61,8	-53,3	2007-6	-66,3
Pennsylvania	-20,2	2009-12	-17,1	-14,8	-9,7	2009-4	-18,7
Rhode Island	56,2	2010-3	42,9	51,1	2,2	2009-3	44,3
South Carolina	-37,7	2009-12	-43,5	-45,8	-59	2009-4	-42,2
South Dakota	-49,4	2009-12	-46,9	-48,3	-60	2007-9	-54,6
Tennessee	-3,3	2010-3	-9,1	-5,8	-26,7	2009-3	-9,8
Texas	-26,5	2010-3	-20,5	-26,9	3,6	2009-4	-21,6
Utah	5,8	2012-12	3,5	-13	-66	2007-6	-14,2
Virginia	65,4	2009-12	71,5	77,5	63,7	2009-10	71,4
Vermont	-60,7	2007-1	-72,1	-73,3	-104	2009-12	-69,8
Washington	-22,7	2009-11	-19,1	-23,9	16,2	2009-7	-18,2
Wisconsin	-59,5	2009-12	-64,9	-62,7	-80,5	2007-12	-72,4
West Virginia	-15,5	2009-11	-5,9	-8,2	-6,3	2007-6	-22,4
Wyoming	57,3	2009-8	73,5	73,5	125,6	2009-8	74,3
Mean Abs. Change	-	-	6,7	6,2	26,1	19,4 m.	6,7
Corr. with Baseline	-	-	0,987	0,991	0,873		0,991

Source*:* Author's estimates

They show similar results as the baseline with an excess shift correlation of 0,987 and a mean absolute change in the excess shift of 6,7%. Column 2 of Table 6 shows that the cross-sectional regression results are robust as the parameter estimates and significance of variables is similar to the baseline.

Table 6: Cross sectional regression results for breakpoint extensions

Independent Variables	Baseline	Aug. 2009 Break	Dec. 2010 Break	BP Estimation	BP Breaks
	(1)	(2)	(3)	(4)	(5)
Population Growth Rate (%/year)	35,125***	25,847**	27,986*	16,832	30,014***
	(12,255)	(11,207)	(15,527)	(11,472)	(11,225)
Urbanization Rate (%)	1,301***	1,413***	1,383**	1,514***	1,394***
	(0,492)	(0,485)	(0,651)	(0,524)	(0,511)
House Price Appreciation Rate (%/year)	6,152**	5,687**	6,508	7,304***	6,402**
	(2,830)	(2,781)	(4,270)	(2,439)	(2,767)
Private Service Share (%)	1,233	1,070	1,405	0,654	1,160
	(2,071)	(2,179)	(3,074)	(2,290)	(2,165)
Manufacturing Share (%)	1,203	0,592	0,859	0,068	0,985
	(2,203)	(2,348)	(3,078)	(2,061)	(2,234)
Construction and Resource Share (%)	10,835***	12,209***	12,793***	13,618***	11,895***
	(2,850)	(2,582)	(3,602)	(3,776)	(2,859)
Midwest	34,295	23,767	31,659	17,107	29,934
	(21,055)	(20,689)	(29,971)	(23,579)	(21,702)
Northeast	59,914**	49,353*	56,394	26,046	54,690*
	(29,835)	(28,734)	(40,367)	(25,440)	(30,518)
South	57,893***	57,113***	63,082**	48,900***	57,695***
	(19,035)	(18,831)	(26,812)	(17,618)	(19,313)
Constant	-377,329***	-359,778**	-398,573*	-346,315**	-380,274***
	(143,629)	(156,891)	(212,391)	(154,445)	(146,692)
Adjusted R^2	0,668	0,659	0,652	0,638	0,663
Residual Std. Error (df = 41)	35,282	35,776	37,696	40,052	36,287
F Statistic (df = 9; 41)	12,155***	11,716***	11,409***	10,801***	11,909***

Note: Sample size is 51. White (1980) robust standard errors in parentheses, *p<0,1; **p<0,05; ***p<0,01.
Source*:* Author's estimates

Second, column 4 of Table 5 shows the excess shift results if each state had a December 2010 breakpoint, which was relatively later than most state shifts. These excess shifts are also highly correlated (correlation: 0,991) and do not change much (mean absolute change of 6,2%) compared to the baseline results. The cross-sectional regression results in column 3 of Table 6 also show little change compared to the baseline results, except house price appreciation has a similar parameter estimate but is no longer statistically significant. Overall, the results are robust to the use of common breakpoints.

Bai and Perron Breakpoints

Beveridge curves can experience multiple breaks, as documented by Diamond & Şahin (2015) and Michaillat & Saez (2021). The possibility of multiple breakpoints in each state's estimation of (9) is explored through the Bai & Perron (1998, 2003) method, which is a method that searches for multiple unknown breakpoints. Their method divides the regression model into K breaks and $K+1$ regimes and modifies the Beveridge curve estimation equation to:

$$\ln\left(\frac{1-u_{i,t}}{u_{i,t}}\right) = \beta_{1,i,k} + \beta_{2,i,k}\ln\left(\frac{v_t}{u_{i,t}}\right) + \epsilon_{i,t} \tag{18}$$

$$t = T_{k-1}, \dots, T_k \qquad k = 1, \dots, K+1.$$

Each regime k has Beveridge curve parameters estimated for each state $\beta_{1,i,k}$ and $\beta_{2,i,k}$. Their method uses an efficient dynamic programming algorithm to identify the optimal breakpoints for each possible number of breaks K and then chooses the number of breakpoints typically based on an information or other criteria[10].

First, the Bai & Perron method is employed in determining structural breakpoints and the associated data window T_{k-1} to T_k for equation (18) in each state. The resulting breakpoints and excess shifts are in columns 5 and 6 of Table 5. This method chooses breakpoints that are an average 19,1 months different than the baseline results. Most (42) states have earlier breakpoints than the baseline results. All states except Maryland have a pre-Great Recession breakpoint that excludes the 2001 recession from the Beveridge curve estimation, which means the Beveridge curve estimates train on a short data window (median 37 months). An outlier adjustment for Louisiana is made since results without the adjustment are implausible[11]. The excess shifts are highly correlated (correlation: 0,873) with the baseline results, but there are some qualitative differences between them. First, Florida accounts for the largest shift in the Beveridge curve with a 144,7% excess shift, as Nevada's excess shift falls to 113,6%. Second, two of the states that account for an inward shift of the Beveridge curve, Michigan (excess shift: -128,9%) and Mississippi (-111,3%), are vulnerable to short sample issues. Michigan's unemployment rate failed to recover from the 2001 recession and hovered near 7% until the Great Recession, while Mississippi's unemployment rate briefly increased by more than 2,5% in the aftermath of Hurricane Katrina, which causes a slight outlier issue like Louisiana. The differences in the excess shifts do not substantially affect the cross-sectional regression results from (15) in column 4 of Table 6, as they are similar to the baseline result, with only the population growth rate losing significance.

Second, the Bai & Perron method is used as an alternative to choosing the states' Great Recession breakpoints only while estimating the Beveridge curve for each state using the full sample before the breakpoint. This method ignores pre-Great Recession breakpoints and shows that the changes in the excess shifts are caused mainly by the loss of the data around the 2001 recession. Despite the significant changes in the breakpoints compared to the baseline, the excess shift results in column 7 of Table 5 are quite similar to the baseline results with a mean absolute excess shift change of 6,7 percentage points and a correlation of excess shifts with those of the baseline of 0,991. The cross-sectional regression results on the excess shifts in column 5 of Table 6 are quite similar to the baseline results. While the results are still generally robust, the risk of using the Bai and Perron method for the Great Recession is losing information for the Beveridge curve estimates that would anchor projections of what would happen during a national recession with a low vacancy rate.

Conclusion

The results in this paper support that there are diverse causes of the Great Recession shift in the Beveridge curve. The decomposition results across states suggest some regional differences in the extent and timing of shifts in the Beveridge curve. Regression results suggest that higher population growth, house price appreciation, urbanization, and construction and natural resource sector employment leading up to the Great Recession led to higher excess shifts, which supports that housing market problems, geographic mismatch, skills mismatch, and other factors could all help explain the Great Recession shift in the Beveridge curve.

---

[10] The Bayesian information criterion is applied, as Bai & Perron (2003) note that the Akaike information criterion tends to overestimate the number of breaks.

[11] Louisiana's initial excess Beveridge curve shift (-4.081%) overstates the outward adjustment relative to other states. The Bai & Perron method identifies March 2005 as a breakpoint, preceding Hurricane Katrina, which raised unemployment from 5.3% in August to over 11% by December (NCEI, 2025). This distortion yields an unrealistically high post–Great Recession unemployment share. Accordingly, the full pre-break sample (Dec 2000–Aug 2007) is retained for projection.

The decomposition method provides a flexible method to study other shifts in the Beveridge curve and their potential causes. For example, it could be used to further study the unusual shape and shifts of the Beveridge curve during the COVID-19 pandemic documented by Lubik (2021), Barlevy et al. (2024), and Cheremukhin & Restrepo-Echavarria (2025). State-level differences in sectoral employment, public health policies, and timing of the pandemic's effects could help explain both outward and inward shifts of the Beveridge curve. With state-level data, the method could be used to examine Beveridge curve shifts within states, which would help local policymakers identify areas and causes of economic duress or study the effects of state labour market policy changes. The method could examine Beveridge curve shifts in and across other countries from recessions and other events so long as their labour markets follow a stable Beveridge curve relationship with area-wide job vacancies and there is enough data before the shifts to estimate this relationship. It also may be used to address the finding from Abraham (1987) that geographic mismatch across regions contributed more than 1% to rising unemployment in the 1970s.

The decomposition results in this paper suggest that only significant differences in shifts between high population states or regions could account for such a large increase in unemployment from geographic mismatch. In addition, the decomposition with benchmarks could be applied to demographic and sectoral groups, such as structural differences in the Beveridge curve by sex as noted in Sheldon (2023). Benchmarks based on mean shares of unemployed in different age groups, industries, or demographic groups could help quantify how much each group contributes to overall shifts in the Beveridge curve, which would guide policymakers to aid those affected by worsening labour market conditions.

Credit Authorship Contribution Statement

Aaron Popp was solely responsible for all aspects of this study, including conceptualization, methodology, data collection, formal analysis, writing, editing, and approval for final publication.

Acknowledgments

We thank seminar participants at California State University, Fullerton for helpful comments and suggestions.

Conflict of Interest Statement

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the author upon reasonable request.

References

Abraham, K. G., & Wachter, M. (1987). Help-wanted advertising, job vacancies, and unemployment. *Brookings Papers on Economic Activity*, 1987(1), 207-248. http://dx.doi.org/10.2307/2534516

Alsalman, Z. (2023). Oil price shocks and US unemployment: evidence from disentangling the duration of unemployment spells in the labor market. *Empirical Economics*, 65(1), 479-511. https://doi.org/10.1007/s00181-022-02351-0

Altavilla, C., & Caroleo, F. E. (2013). Asymmetric effects of national-based active labour market policies. *Regional Studies*, 47(9), 1482-1506. http://dx.doi.org/10.1080/00343404.2011.635139

Barlevy, G., Faberman, R. J., Hobijn, B., & Şahin, A. (2024). The shifting reasons for Beveridge curve shifts. *Journal of Economic Perspectives*, 38(2), 83-106. http://dx.doi.org/10.1257/jep.38.2.83

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1) 47-78. http://dx.doi.org/10.2307/2998540

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1-22. http://dx.doi.org/10.1002/jae.659

Begen, N., Mercan, M. A., & Barlin, H., (2023). Immigration, job vacancies, and Beveridge Curve: Evidence from Syrian refugees in Turkey. *The Economic and Labour Relations Review*, 34(2), 279-298. http://dx.doi.org/10.1017/elr.2023.4

Blanchard, O. J., & Diamond, P. A. (1989). The aggregate matching functions. *NBER Working Paper* No. 3175. https://www.nber.org/system/files/working_papers/w3175/w3175.pdf

Böheim, R., & Christl, M. (2022). Mismatch unemployment in Austria: the role of regional labour markets for skills. *Regional Studies, Regional Science*, 9(1), 208-222. http://dx.doi.org/10.1080/21681376.2022.2061867

Bova, E., Tovar Jalles, J., & Kolerus, C. (2018). Shifting the Beveridge curve: What affects labour market matching? *International Labour Review*, 157(2), 267-306. http://dx.doi.org/10.1111/ilr.12046

Cheremukhin, A., & Restrepo-Echavarria, P. (2025). The dual Beveridge curves. *SSRN Working Paper* 4973944. http://dx.doi.org/10.24149/wp2221

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, 28(3), 591-605. http://dx.doi.org/10.2307/1910133

Clinger, A., & Rodgers, J. (2010). The impact of the 2007-2010 financial crisis on the State of Nevada. The Financial Crisis Inquiry Commission 2010. https://elischolar.library.yale.edu/ypfs-documents/5881

Davis, S. J., Faberman, R. J., & Haltiwanger, J. C. (2013). The establishment-level behaviour of vacancies and hiring. *The Quarterly Journal of Economics*, 128(2), 581-622. http://dx.doi.org/10.1093/qje/qjt002

Destefanis, S., & Fonseca, R. (2007). Matching efficiency and labour market reform in Italy: A macro econometric assessment. *Labour*, 21(1), 57-84. http://dx.doi.org/10.1111/j.1467-9914.2006.00368.x

Destefanis, S., Fragetta, M., & Ruggiero, N. (2023). Active and passive labour-market policies: the outlook from the Beveridge curve. *Applied Economics*, 55(55), 6538-6550. https://doi.org/10.1080/00036846.2022.2159010

Diamond, P. A. (1982). Wage determination and efficiency in search equilibrium. *The Review of Economic Studies*, 49(2), 217-227. http://dx.doi.org/10.2307/2297271

Diamond, P. A., & Şahin, A. (2015). Shifts in the Beveridge curve. *Research in Economics*, 69(1), 18-25. http://dx.doi.org/10.1016/j.rie.2014.10.004

Dickens, W. T. (2009). A New Method for Estimating Time Variation in the NAIRU. In: Fuhrer, J., Kodrzycki, Y., Little, J., and Olivei, G. (Eds.). *Understanding inflation and the implications for monetary policy: A Phillips curve retrospective* (pp. 205-228). Cambridge, Massachusetts: MIT Press. http://dx.doi.org/10.7551/mitpress/9780262013635.003.0021

Dixon, R., Lim, G. C., & Freebairn, J. (2014). Regional Beveridge Curves: A latent variable approach. *Regional Studies*, 48(2), 254-269. http://dx.doi.org/10.1080/00343404.2011.644238

Elsby, M. W., Michaels, R., & Ratner, D. (2015). The Beveridge curve: A survey. *Journal of Economic Literature*, 53(3), 571-630. http://dx.doi.org/10.1257/jel.53.3.571

Federal Open Market Committee (2013). Meeting of the Federal Open Market Committee on March 19, 2013. https://www.federalreserve.gov/monetarypolicy/files/FOMC20130320meeting.pdf

Famiglietti, M., Garriga, C., & Hedlund, A. (2020). The Geography of Housing Market Liquidity During the Great Recession. *Federal Reserve Bank of St. Louis Review*, 102(1), 51-78. http://dx.doi.org/10.20955/r.102.51-77

Figura, A., & Waller, C. (2024). What does the Beveridge curve tell us about the likelihood of soft landings? *Journal of Economic Dynamics and Control*, 169, 104957. https://doi.org/10.1016/j.jedc.2024.104957

Flora, P. (2016). Regional Spotlight: The State of the States. *Regional Spotlight of the Federal Reserve Bank of Philadelphia*, 2016(Q4), 8-15. https://fedinprint.org/item/fedpei/23684

Ghayad, R. (2013). A decomposition of shifts of the Beveridge curve. *Federal Reserve Bank of Boston Public Policy Brief*, 13-1. http://dx.doi.org/10.2139/ssrn.2308071

Ghayad, R., & Dickens, W. (2012). What can we learn by disaggregating the unemployment-vacancy relationship? *Federal Reserve Bank of Boston Public Policy Brief*, 12-3. http://dx.doi.org/10.2139/ssrn.2285075

Glaeser, E. L., Gyourko, J., & Saiz, A. (2008). Housing supply and housing bubbles. *Journal of Urban Economics*, 64(2), 198-217. http://dx.doi.org/10.1016/j.jue.2008.07.007

Gökten, M., Heimberger, P., & Lichtenberger, A. (2024). How far from full employment? The European unemployment problem revisited. *European Economic Review*, 164, 104725. https://doi.org/10.1016/j.euroecorev.2024.104725

Holmes, M. J., & Otero, J. (2020). The Beveridge curve across US states: new insights from a pairwise approach. *Oxford Bulletin of Economics and Statistics*, 82(2), 405-424. http://dx.doi.org/10.1111/obes.12337

Karahan, F., & Rhee, S. (2019). Geographic reallocation and unemployment during the Great Recession: The role of the housing bust. *Journal of Economic Dynamics and Control*, 100(March 2019), 47-69. https://doi.org/10.1016/j.jedc.2018.12.007

Karaki, M. B. (2018). Oil prices and state unemployment rates. *The Energy Journal*, 39(3), 25-50. https://doi.org/10.5547/01956574.39.3.mkar

Kindberg-Hanlon, G., & Girard, M. (2024). What Caused the Beveridge Curve to Shift Higher in the United States During the Pandemic? International Monetary Fund Working Paper WP/24/8. http://dx.doi.org/10.5089/9798400263415.001

Kosfeld, R., Dreger, C., & Eckey, H. F. (2008). On the stability of the German Beveridge curve: a spatial econometric perspective. *The Annals of Regional Science*, 42, 967-986. http://dx.doi.org/10.1007/s00168-007-0190-y

Leduc, S., & Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82, 20-35. http://dx.doi.org/10.1016/j.jmoneco.2016.07.002

Lincaru, C. (2010). Regional mismatch tendencies in Romania-evidence from Beveridge Curve. *Romanian Journal of Regional Science*, 4(2), 32-61. https://www.researchgate.net/publication/228883805_Regional_mismatch_tendencies_in_Romania-evidence_from_Beveridge_Curve

Lubik, T. A. (2021). Revisiting the Beveridge curve: why has it shifted so dramatically? *Richmond Fed Economic Brief*, 21(36). https://www.richmondfed.org/publications/research/economic_brief/2021/eb_21-36

McPherson, S. H., & Flores, O. (2012). Provincial disparities and structural unemployment in Canada. *Regional and Sectoral Economic Studies*, 12(1), 25-42. https://www.usc.es/economet/reviews/eers1212.pdf

Michaillat, P., & Saez, E. (2021). Beveridgean unemployment gap. *Journal of Public Economics Plus*, 2, 100009. http://dx.doi.org/10.1016/j.pubecp.2021.100009

Mortensen, D. T., & Pissarides, C. A., 1994. Job creation and job destruction in the theory of unemployment. *The Review of Economic Studies*, 61(3), 397-415. http://dx.doi.org/10.2307/2297896

National Centers for Environmental Information (NCEI). (2025). Costliest US Tropical Cyclones. https://www.ncei.noaa.gov/access/billions/dcmi.pdf

Nota, M. (2008). Estimation of the Slovak Beveridge curve using regional data. University of Delaware. https://www.proquest.com/dissertations-theses/estimation-slovak-beveridge-curve-using-regional/docview/304629372/se-2?accountid=9840

Parker, E. & Marshall K. (2017). Nevada's Great Recession: Looking Back, Moving Forward. Reno, NV: University of Nevada Press. ISBN-13: 978-0874175974

Petrongolo, B., & Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature*, 39(2), 390-431. http://dx.doi.org/10.1257/jel.39.2.390

Pissarides, C. A. (1985). Short-run equilibrium dynamics of unemployment, vacancies, and real wages. *The American Economic Review*, 75(4), 676-690. https://www.jstor.org/stable/1821347

Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American Statistical Association*, 55(290), 324-330. http://dx.doi.org/10.1080/01621459.1960.10482067

Şahin, A., Kitao, S., Cororaton, A., & Laiu, S. (2011). Why small businesses were hit harder by the recent recession. *Current Issues in Economics and Finance*, 17(4). http://dx.doi.org/10.2139/ssrn.1895527

Şahin, A., Song, J., Topa, G., & Violante, G. L. (2014). Mismatch unemployment. *American Economic Review*, 104(11), 3529-3564. http://dx.doi.org/10.1257/aer.104.11.3529

Samson, L. (1994). The Beveridge curve and regional disparities in Canada. *Applied Economics*, 26(10), 937-947. http://dx.doi.org/10.1080/00036849400000101

Sheldon, H. (2023). The Beveridge Curve and the "she-cession". *Journal of Business and Economic Studies*, 26(2), 56-71. https://jbes.scholasticahq.com/article/70274.pdf

Walden, M. L. (2014). Recovery from the Great Recession: Explaining differences among the states. *Journal of Regional Analysis and Policy*, 44(2), 166-174. https://doi.org/10.22004/ag.econ.243972

Wall, H. J., & Zoega, G., 2002. The British Beveridge curve: A tale of ten regions. *Oxford Bulletin of Economics and Statistics*, 64(3), 257-276. http://dx.doi.org/10.1111/1468-0084.00019

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4), 817-838. https://doi.org/10.2307/1912934